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Research Paper

The influence of firm efficiency on agency credit ratings

Dafydd Mali[1] and Hyoung-Joo Lim[2]

[1]Sheffield Business School, Sheffield Hallam University, City Campus, Howard Street, Sheffield S1 1WB, UK; email: d.mali@shu.ac.uk

[2]Division of Accounting/Tax and Management Information Systems, Kyonggi University, 154-42 Kyangkyosan ro, Youngtong gu, Suwon, Kyonggi, South Korea; email: limhj@kgu.ac.kr

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ABSTRACT

This paper examines the relationship between relative efficiency and credit ratings using a sample of Korean listed firms and finds a positive relationship in the subsequent period after adjusting for absolute efficiency. The results suggest that credit rating agencies consider relative efficiency as a variable that influences a firm's ability to survive a business cycle. Interestingly, when we divide our samples into investment-grade and non-investment-grade firms, we find a different relationship. While we continue to find consistent results for the investment-grade group, we find a negative relationship between relative efficiency and credit ratings for non-investment-grade firms. We suggest "higher" levels of efficiency by non-investment-grade firms can be considered opportunistic or a form of distress, and potentially be the result of ineffective decision making. We conjecture that credit rating agencies have the ability to impose penalties of lower credit ratings on firms that engage in such behavior.

Keywords: relative efficiency; credit ratings; credit risk; frontier analysis.

Corresponding author: H.-J. Lim

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1 INTRODUCTION

The role of a credit rating agency is to provide market participants with information about whether a firm is likely to survive through a business cycle (Carey and Hrycay 2001). We believe that firms with higher relative efficiency than their peers are more likely to withstand the stressful macroeconomic conditions that can cause a firm to default. A firm's relative efficiency is an estimate of operational performance: higher operational performance demonstrates that a firm's management has been effective in generating the maximum number of sales from given resources. Consequently, credit rating agencies have the potential to capture management's effective utilization of resources and include this information in a firm's credit rating. Thus, we perform empirical tests to evaluate whether relative efficiency can be considered a key determinant when estimating credit ratings. While we do not explicitly test the relationship between operational performance (relative efficiency) and effective decision making (strategic management), we consider there to be an implicit relationship between the two based on the assumption that management's ability to make effective decisions reduces inefficiency. Debtholders, firms and market participants pay close attention to credit ratings: debtholders depend on credit ratings in order to monitor the security of their investment; firms would prefer to have higher credit ratings because they are required to pay lower interest yields on debt. Therefore, whether credit ratings reflect a firm's overall operational performance (proxied by relative efficiency) is an important question for market participants.

A firm's efficiency level is determined by changes in output ($\text{sales}_t - \text{sales}_{t-1}$) divided by changes in input ($\text{costs}_t - \text{costs}_{t-1}$). Firms can influence their efficiency ratio in two different ways: output maximization or input minimization. A firm can maximize output using a number of techniques, including effective promotional activities, understanding their markets and market trends, effective pricing strategies, and through the adoption of new technologies. Firms can also improve their efficiency score by minimizing input levels using a number of different techniques, for instance, effective utilization of resources, efficient manufacturing and keeping their labor force at an optimum level. A firm with the ability to effectively implement such strategies should demonstrate superior operational performance relative to their peers. We conjecture that efficiency positively influences a firm's credit rating based on the belief that rating agencies consider relative efficiency to be a variable that influences default risk.

A firm's credit rating is based on a spectrum ranging from AAA to D. However, regulators, financial institutions and numerous academic studies treat non-investment-grade (NIG) and investment-grade (IG) firms separately due to their differing risk structures (Becker and Milbourn 2011; Bolton *et al* 2012; Opp *et al* 2013; Alissa *et al* 2013; Kraft 2015). We speculate that, given that financial institutions consider IG and NIG firms to be different, there may be differences in their business operations. Compared with NIG firms, IG firms are potentially more likely to have the ability to optimize efficiency through robust strategic management systems that keep their operational performance at a higher level. NIG firms may reduce inputs in order to increase efficiency because they have less ability to raise output (sales). In this study, we compare the relative efficiency of firms using frontier analysis – specifically data envelopment analysis (DEA) – to capture the relationships between efficiency and credit ratings for both groups. We speculate that there are potentially different phenomenons explaining the relationship between efficiency, operational performance and credit ratings for both groups. IG firms at the optimum efficiency frontier should have a strategic management system in place in order to maximize operational efficiency. NIG firms have the potential to opportunistically minimize required operational expenses and resources in order to meet financial targets. Consequently, while the latter firms are theoretically closer to the optimal efficiency frontier horizon, this position could be achieved through opportunistic reductions in required resources and weak operational performance, or as a result of economic distress.

Our study is motivated by three questions. First, we investigate whether relative efficiency has explanatory power regarding the relationship between firm efficiency and credit ratings. Previous literature partitions efficiency studies into two fields based on two different methodological approaches:

(1) absolute efficiency using financial ratio (eg, asset turnover $=$ sales/total assets, return on total assets $=$ earnings before interest and taxes/total net assets (or ROTA $=$ EBIT/TA)); and

(2) relative efficiency studies based on frontier analysis techniques (relative efficiency scores are compared with industry peers of the same period).

Borrowing from the Ohlson (1995) model, studies by Fairfield and Yohn (2001) and Soliman (2008) demonstrate a positive relationship between efficiency using financial ratios and firm performance. Absolute-efficiency-based financial ratios, such as return on assets (ROA), are generally interpreted as a measure of "operating efficiency". However, critics of the absolute efficiency methodology suggest that the technique leads to bias. Using frontier analysis, there is evidence suggesting that firm efficiency has a significant positive influence on firm performance (Alam and Sickles 1998; Greene and Segal 2004) and that efficiency changes based on frontier analysis are incrementally informative compared to financial ratios (Baik *et al* 2012; Demerjian *et al* 2012; Frijns *et al* 2012). Firms can choose numerous different inputs in order to create outputs. DEA is considered advantageous because it allows differential weightings of inputs that are likely to yield a more accurate measurement than financial ratios. DEA analysis distinguishes between random shocks and technical inefficiencies in the production function, while simple financial ratios cannot. Given the lack of previous studies linking relative efficiency and credit ratings, we are interested in examining whether there is a statistically significant relationship between relative efficiency and credit ratings in the subsequent period after adjusting for absolute efficiency and other key determinants.

Second, we are curious whether credit rating agencies can capture a firm's relative efficiency and compound this information with a firm's credit rating. Third, we question whether the relationship between relative efficiency and credit ratings is different for investment-grade and non-investment-grade firms. Banks and suppliers use credit ratings when issuing terms for payment, and consider NIG and IG firms to be fundamentally different. There is evidence to prove that firms would take action to manage leverage (Kisgen 2009; Hovakimian and Hovakimian 2009) and earnings (Ali and Zhang 2008; Jung *et al* 2013) in order to influence a credit rating agency's perception of default risk. These strategies are found to be more prominent when firms are closer to the investment-grade threshold (Alissa *et al* 2013). These decisions would improve a firm's efficiency level, but managing leverage and earnings would lead to weaker operational performance and fail to achieve financial targets. Thus, we are also motivated by whether it is possible to capture different relationships between efficiency and credit rating levels for IG and NIG firms.

Using a sample of 14 720 Korea Stock Exchange (KRX) firm–year observations from 2000 to 2015, our ordered probit regression analysis suggests that relative efficiency computed from frontier analysis has a statistically significant positive relationship with credit ratings in the subsequent period, after adjusting for absolute efficiency. The results suggest that relatively more efficient firms are able to achieve higher credit ratings than less efficient firms. Our results are consistent when replacing relative efficiency scores with decile ranks. When using an interaction term for our relative efficiency score and an IG dummy that divides our sample into investment-grade and non-investment-grade groups, we find evidence suggesting that the relationship between relative efficiency and credit ratings is stronger for investment-grade firms. Overall, the results suggest that relative efficiency has the explanatory power to illustrate the relationship between firm efficiency and credit ratings in the subsequent period.

Next, we partition our sample into IG and NIG samples and repeat the analysis. While we find a consistent positive relationship when using the IG sample, we find a negative relationship between relative efficiency and credit ratings for NIG firms, suggesting that firm efficiency negatively influences credit ratings for the NIG group. Our interpretation of this result is that the high efficiency achieved by NIG firms has the potential to be influenced by opportunistic managerial decisions and is not a reflection of true efficiency levels. It is possible that managers of NIG firms may have engaged in input-manipulation activities, such as reducing necessary expenditure (eg, advertising, research and development (R&D), workforce), downsizing in order to increase short-term efficiency. Consequently, this form of efficiency may be captured and punished by credit rating agencies. Our results are robust with various forms of additional analysis.

Our study contributes to the literature in several ways. First, we provide evidence that relative efficiency computed using DEA is informative in predicting credit ratings in the subsequent period and provides additional information when included with absolute efficiency. Second, we find different relationships between firm efficiency and credit ratings for investment-grade and non-investment-grade firms. We suggest that both groups have potentially different capabilities and incentives that result in superior or inferior operational performance. NIG firms may demonstrate efficiency through manipulation of short-term input decisions. We infer from this that inferior decision making is manifested in a firm's efficiency ratio and leads to a credit rating reduction in the subsequent period. To the best of our knowledge, we are the first to examine the relationship between relative efficiency and credit ratings and find different relationships between credit ratings and efficiency based on a firm's credit rating status. Our results may be of interest to credit rating agencies, debtholders, shareholders and other market participants who believe the link between efficiency determined by the decisions of management and credit ratings determined by agencies is important.

The remainder of this paper is organized as follows. In Section 2, we review the relevant literature and develop hypotheses. In Section 3, we explain our research design and variable estimation. In Section 4, we report the results of our empirical analysis. We include additional analyses for robustness in Section 5. Section 6 provides a summary of our main findings and conclusions.

2 LITERATURE REVIEW AND HYPOTHESES

2.1 Literature review on credit ratings

Credit rating agencies provide information to market participants about a firm's potential risk of financial default. Ratings analysts base their rating decisions primarily on financial data that includes a comparative assessment of a firm's financial strength, leverage, profitability, size and stability (Hovakimian *et al* 2001; Hovakimian and Hovakimian 2009; Kraft 2015). In addition, credit rating agencies analyze "soft data", a combination of management quality, internal controls, corporate governance and industry structure (Moody's Investor Service 2018). The purpose of a credit rating is to provide investors, government agencies and stakeholders with an "economically meaningful" assessment of a firm's strength relative to its peers (Boot *et al* 2006). In South Korea, the four largest credit rating agencies – NICE Group, Korea Investors Service (KIS), SCI Information Service Inc and Korea Ratings (KR) – offer an ordinal rank of downside risk consistent with the international credit rating agencies Standard and Poor's (S&P) and Moody's. Credit ratings are divided into ten broad categories with increasing levels of risk (AAA, AA, A, BBB, BB, B, CCC, CC, C and D). Each broad category is further grouped by $\pm$ notches. Firms with the same ordinal rank are considered to have similar levels of credit risk (Kisgen 2006; Boot *et al* 2006).

Banks and insurance companies can only hold IG bonds, due to regulatory constraints (Becker and Milbourn 2011); credit rating agencies require IG firms to comply with strict rating-contingent regulation (Bolton *et al* 2012). Several studies consider different levels of risk for investment-grade and non-investment-grade firms (Opp *et al* 2013; Kraft 2015). The distinction between IG and NIG is due to differences in their corporate systems, performance, governance and ability to withstand economic distress. There are various advantages associated with IG status. NIG firms that straddle the investment-grade threshold would likely enjoy more favorable fees from suppliers, more investment, lower rates and reputational advantages. Jung *et al* (2013) find that earnings smoothing via earnings management is higher when firms have the potential to straddle specific thresholds. Ali and Zhang (2008) find evidence that $\mp$ notch category firms use higher levels of earnings management than middle category firms, in order to influence a credit ratings upgrade/downgrade. Further, Alissa *et al* (2013) show that earnings management is higher for firms below the investment-grade threshold. The evidence suggests that managers have incentives to modify their credit ratings; however, firms are likely unable to facilitate an increase based on agencies' knowledge of such behavior. Using a South Korean sample, Mali and Lim (2016) show South Korean credit rating agencies differentiate between IG and NIG samples based on "equal" governance structures. They find IG firms with higher levels of institutional ownership have higher credit ratings, consistent with large owners demanding robust governance systems. However, large institutional ownership is shown to have a negative influence on credit ratings for NIG firms, potentially due to weaker governance systems and the potential for wealth expropriation. Their results suggest that South Korean credit rating agencies do not consider IG and NIG firms to be equal.

We believe that relative efficiency has important characteristics for market participants and may signal financial default to credit rating agencies. To different degrees, based on credit rating status, firms have the potential to manage earnings in order to meet financial targets, but relative efficiency, calculated using frontier analysis, establishes the optimal ratio of the available inputs required in order to generate sales. Deviations from the optimal efficiency frontier for the IG sample will have an underlying effect on operational performance. However, the mechanisms by which

IG and NIG firms influence the efficiency ratio to meet financial targets may be different. NIG firms may not have developed robust strategic management or governance systems and may engage in earnings management to meet financial targets or reduce required expenses that mechanically increase the efficiency ratio, which has a negative effect on operational performance. Whether or not credit rating agencies may be sophisticated enough to capture potentially different behavior for NIG and IG firms is unknown.

2.2 Literature review on firm efficiency

The firm efficiency literature is devoted to finding a relationship between firm efficiency and profitability by using one of two methods: simple accounting ratios or frontier analysis. Using simple accounting ratios to estimate efficiency, Ou and Penman (1989) find a positive relationship between firm efficiency and future earnings. Fairfield and Yohn (2001) find evidence that changes in asset turnover are more persistent in profit margins, thus increasing with firm value. Penman and Zhang (2002) show that asset turnover is related to current and future earnings changes. While absolute models are considered appealing due to their relative computational simplicity, frontier analysis is considered to be a more precise measure. Numerous studies examine the relationship between firm performance and "relative" efficiency using frontier analysis. Greene and Segal (2004) demonstrate that firms with higher operational efficiency than their peers are more profitable, suggesting that firms further away from the efficiency frontier horizon are less profitable using ROA and return on equity (ROE). Cummins and Xie (2008) use DEA in order to examine how efficiency and productivity influence mergers and acquisitions in the US property-liability insurance industry. They find a positive association between efficiency and revenue gains. Baik *et al* (2013) use DEA and stochastic frontier analysis (SFA) to examine the relationship between operational efficiency and changes in current and future profitability (after adjusting for absolute efficiency). They find evidence that efficiency change is positively associated with both current and future changes. Further, they find evidence that these changes are reported in analysts' forecast revisions. Their model, which includes absolute efficiency and relative efficiency, suggests that relative efficiency has additional explanatory power for empirical modeling purposes.

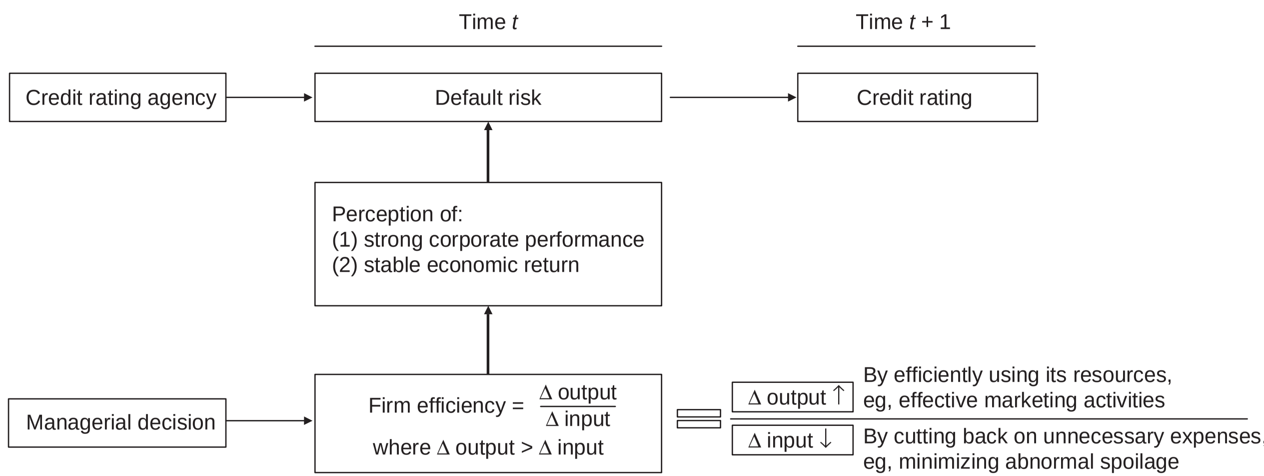
Frontier analysis can be performed using two different empirical tests: DEA (a non-parametric approach) and SFA (a parametric approach). Frontier analysis is considered more robust than absolute measures for several reasons. First, relative efficiency is estimated as the overall level of outputs divided by inputs for each decision-making unit (DMU); thus, the most efficient firm within a group of DMUs can be estimated for each industry and firm year because the DEA vector is industry/year specific. After estimating the DEA vector for a specific industry within a year, it is possible to combine the vector with equivalent vectors and years. Second, frontier analysis considers the optimum level of various inputs required to generate sales; absolute ratios divide sales by assets or equity. However, the optimum level of expenditure and resources required in order to generate sales can never be known using absolute measures. For example, the salary expense of a professional sports team is likely much higher than that of a ship manufacturer. Relative efficiency enables the partitioning of the inputs required to generate output (sales) into two components: given resources and costs. Costs are made up of expenditures incurred in order to generate revenue, including advertising, R&D, administration and the cost of goods sold. Given resources consist of a firm's equity, including property, plants and equipment, operating lease and goodwill and other intangibles. Using a technique such as DEA, it is possible to find the level required to achieve optimum efficiency for each input. Third, while different weightings are applied in order to discover the maximum efficiency frontier, it is possible to compare all firms within the sample using an ordinal rank. Further discussion about the advantages of frontier analysis over absolute measures is provided by Demerjian *et al* (2012) and Frijns *et al* (2012).

2.3 Hypotheses

Figure 1 illustrates our hypothesis. The strategic decision making of management is manifested in operational performance on a daily basis. Firms that achieve maximum outputs from given inputs are more efficient because of superior decision making relative to their peers. Firms have the potential to improve efficiency using two techniques: operational efficiency and technical efficiency. Firms with robust operational efficiency are able to achieve greater output by maximizing sales. Firms have the potential to maximize sales through effective advertising and marketing campaigns, strong products and pricing strategies, and the ability to keep staff motivated, to predict market trends and to adopt new technologies. A firm can increase technical efficiency by reducing costs such as research and administration expenses, and by keeping production levels and labor costs at their optimum; moreover, these firms are likely to have robust production and procurement systems. It is logical that credit rating agencies should consider firms that maximize outputs from given inputs less risky than those with lower relative efficiency.

Consequently, given the association between efficiency, operational performance and the potential for financial default, we expect to find a positive relationship between efficiency and credit ratings using DEA. This would suggest that firms with robust operational performance signal lower future credit risk to credit rating agencies, and this information will be included in a firm's future credit rating. Moreover, we expect to find a positive relationship between credit ratings and relative efficiency

FIGURE 1 Firm efficiency and credit rating.



after adjusting for absolute efficiency. Based on the above, we develop the following hypothesis.

(H1) More efficient firms are able to achieve higher credit ratings than their peers in the subsequent period.

Using our second hypothesis, we aim to discover whether there is a different relationship between efficiency and credit ratings for NIG and IG firms. NIG firms can be considered a riskier investment than IG firms (Bolton *et al* 2012; Opp *et al* 2013; Alissa *et al* 2013). In hypothesis (H1), we consider that efficient firms maximize efficiency through effective strategic management and the ability to generate sales from given resources, eg, through effective sales generation strategies and the effective utilization of resources. While we do not consider IG and NIG firms to be monolithic, we hypothesize that the relationship between relative firm efficiency and credit ratings in the subsequent period may be different for IG and NIG because NIG firms may have less developed corporate systems and potentially less effective strategic management compared with IG firms.

On the one hand, an IG firm is more likely to maximize its output by keeping input levels at an optimum. On the other hand, NIG firms have the potential to reduce important and necessary expenses such as labor, promotional and R&D expenses in order to meet targets. Given that relative efficiency provides an efficiency frontier horizon based on all the resources required to generate sales, the optimum levels of all expenditures and given resources can be estimated. Credit rating agencies are likely able to identify firms that attempt to meet this target opportunistically. For example, if there is an established optimum frontier within an industry for expenditure on R&D, an NIG firm may reduce its R&D expenditure, creating savings in order to decrease input and maximize its efficiency score. We predict that credit rating agencies have the sophistication to consider such behavior a form of distress rather than robust strategic decision making when undertaken by an NIG firm. Based on this scenario, credit rating agencies would capture and impose penalties on such behavior. However, there is also the potential that credit rating agencies are unable to capture such deviations toward the optimum efficiency frontier horizon and will reward NIG firms that reduce required expenditures. Based on the above, we develop the following bidirectional hypothesis.

(H2) The relationship between relative efficiency and credit ratings will be different for NIG and IG firms.

TABLE 1 Credit ratings coding.

CR	IG/NIG	Grade	Definition	Moody's	S&P
10	IG	Best grade	Extremely strong	Aaa	AAA
9		High grade	Very strong	Aa1, Aa2	AA+, AA
8			Strong	Aa3	AA−
7		Middle grade	Good	A1, A2	A+, A
6			Medium	A3	A−
5			Less vulnerable	Baa1, Baa2	BBB+, BBB
4	NIG	Low grade	More vulnerable	Baa3	BBB−
3		Poor grade	Currently vulnerable	Ba, B, Caa	B, C, CCC
2			Highly vulnerable	Ca	C
1			Extremely vulnerable	C	D

3 RESEARCH DESIGN

3.1 Variable definition

Our dependent variable is a firm's credit rating in period $t + 1$. A firm's credit rating is collected from KISVALUE (a Korean database that includes the financial data of Korean listed firms). Since a rating score of 1 is the highest credit rating score in the raw data, we subtract each credit rating score from 11 in order to ease the interpretation of our statistical analysis. As a result, the highest number (10) becomes the highest credit rating (CR) score, and the lowest number (1) is now the lowest credit rating score. We conduct ordered probit regression and thus estimate an ordinal rank for credit rating levels. Table 1 explains our credit rating ordinal ranking, on a decreasing scale. For example, firms with the highest credit ratings, AAA, are given an ordinal score of 10. These firms can be considered extremely strong and have the lowest credit risk. Firms with AA+ and AA ratings are given an ordinal rank of 9 and have slightly higher credit risk from an agency's perspective. This process continues for all credit ratings down to the lowest rank, 1. These NIG firms have a C credit rating by Moody's and a D credit rating by S&P and are considered to have the highest credit risk. See Table 1 for further details.

Altman and Rijken (2006) find that the most important consideration for credit rating agencies is rating stability. Credit ratings are only modified when agencies are confident that changes in a firm's risk profile are permanent, a policy known as the "prudent rating migration" (Hovakimian and Hovakimian 2009; Altman and Rijken 2004; Becker and Milbourn 2011). A credit rating increase can have a long-term effect on a firm's excess equity returns; thus, changes should only be made when there is enough evidence to warrant them. In this study, we examine the relationship between firm efficiency and credit ratings in period $t + 1$ because we surmise that credit rating agencies are forward-looking and have a desire to keep credit ratings relatively consistent. Consequently, operational performance in period t should influence credit ratings in period $t + 1$. However, for completeness, in our additional analyses we repeat all tests using credit ratings in period t.

DEA is a statistical technique used to evaluate relative efficiency for individual decision-making units. Each DMU has a strategic goal to maximize margins by converting inputs into sales. DEA is similar to other efficiency measures (such as return on capital employed and ROA) in the sense that it is an estimation of outputs divided by inputs. However, DEA is different from simple ratio analysis because it provides an ordinal rank of relative efficiency based on the maximum efficiency frontier horizon (industry and market). The values are based on the various sources of available inputs required in order to generate sales. Our DEA efficiency measure is estimated as follows:

$$\frac{\sum_{i=1}^{s} u_i y_{ik}}{\sum_{j=1}^{m} v_j x_{jk}}, \quad k = 1, \dots, n. \tag{3.1}$$

We define output s as sales, and the m inputs are the resources available to the firms in order to achieve output. We include different inputs x in our study. Each output is weighted in order to estimate our efficiency score. The weightings in (3.1) are denoted by u and v for output y and inputs x, respectively. To calculate the DEA vector,

(i) we group each DMU by firm and industry,

(ii) we vary the weights of u and v to maximize (3.1), which estimates the efficiency frontier horizon (the most efficient combination of input resources required in order to generate maximum output),

(iii) after establishing the optimal weights, we multiply the weights by their input and output quantities.

Relative efficiency, $\text{REff}_{i,t}$, is calculated in (3.2): the numerator is sales (output); the denominator is the input, including the given resources each firm requires in order to generate sales. Given resources are property, plants and equipment, operating lease, goodwill and other intangibles. Costs are the expenditures required in order to generate revenue, including advertising, R&D, administration expenses and cost of goods sold. A value of 1 represents the efficiency frontier, to enable an ordinal ranking. A score of 1 is consequently considered the most efficient (10 output/10 input, given a maximum efficiency score of 10). A firm with an ordinal efficiency score of 0.5 (5 output/10 input) is considered to have greater efficiency than one with 0.4

(4 output/10 input). This model allows us to compare first the most efficient combination of input resources for each industry and then each firm's efficiency score with the market as a whole.

Relative efficiency (using DEA) is defined as

$$\max_{u} \theta = \frac{u_1 \text{ sales}}{u_1 \text{GR} + u_2 \text{ costs}}, \tag{3.2}$$

where "sales" (output) denotes gross sales; given resources (GR) is equal to PPE plus operating lease plus goodwill and other intangibles; "costs" denotes the cost of goods sold plus selling, general and administrative expenses (SG&A); PPE denotes net property, plant and equipment; "operating lease" denotes net operating lease; and "goodwill" denotes purchased goodwill.

Equation (3.3) below is our main model of interest. Due to the discrete and ordered nature of our dependent variable – credit ratings (from 1 to 10) – ordinary least squares regression would be an inappropriate model. We therefore borrow from Blume *et al* (1998) and Amato and Furfine (2004) by running ordered probit regression analysis. We define $R_{i,t+1}$ to be the credit rating category of firm i in year $t+1$, and $X_{i,t}$ to be the vector of observable variables available at time t that influence the determination of the credit rating (CR) of firm i. $R_{i,t+1}(\text{CR}_{t+1})$ is continuous and its range is the set of real numbers (see Table 3(b)).

We then consider an unobservable variable

$$R^*_{i,t+1} = \beta X_{i,t} + \varepsilon_{i,t}$$

determined by $X_{i,t}$, where β is the vector of slope coefficients of our explanatory variables. The random variable $\varepsilon_{i,t}$ is a normally distributed unobserved error term; the parameters μ_i define the partitions of the range of $R^*_{i,t+1}$ associated with each value of a rating:

$$R_{i,t} = \begin{cases} 1 & \text{if } R^*_{i,t+1} \leqslant \mu_1, \\ 2 & \text{if } \mu_1 < R^*_{i,t+1} < \mu_2, \\ 3 & \text{if } \mu_2 < R^*_{i,t+1} < \mu_3, \\ & \quad \vdots \\ 10 & \text{if } \mu_9 < R^*_{i,t+1}. \end{cases}$$

We detect the influence of relative efficiency on credit ratings by calculating the marginal effects of the explanatory variables on the probability of ratings changes. We believe firms with the ability to make effective decisions to transform resources into sales are more likely to achieve higher credit ratings in the subsequent period. Thus, we expect to find a positive relationship between firm efficiency and credit

TABLE 2 Model selection process. [Table continues on next page.]

(a) Selection of proxies

Key determinants of CR	Proxies
Firm performance, value	**EPS**, **CFO**, **Tobin's Q**, CPS, ROA, ROS, ROE
Size	**Market size,** investment grade
Lev	**Total liabilities/total assets** Total liabilities/total owners' equity
Loss	**Negative NI**, negative OI
Market risk	**Market volatility**, Beta
Accrual-based earnings management	DAMJ (from modified Jones modes, 1995) DAKO (from performance adjusted model, 2005) **ABMJ (absolute value of DAMJ)** ABKO (absolute value of DAKO)
Real earnings management	**TRM (real earnings management measures)**
Ownership structure	**Biggest owners' shareholdings**
Monitoring	**Foreign investor** Institutional investors

ratings in period $t + 1$. The ordered probit model is specified as follows (see also Table 2):

$$\begin{aligned} R^*_{i,t+1} = {} & \beta_1 \mathrm{REff}_{i,t} + \beta_2 \mathrm{AEff}_{i,t} + \beta_3 \mathrm{CFO}_{i,t} + \beta_4 \mathrm{TQ}_{i,t} \\ & + \beta_5 \mathrm{Lev}_{i,t} + \beta_6 \mathrm{loss}_{i,t} + \beta_7 \mathrm{vol}_{i,t} + \beta_8 \mathrm{AEM}_{i,t} \\ & + \beta_9 \mathrm{REM}_{i,t} + \beta_{10} \mathrm{BigOwn}_{i,t} + \beta_{11} \mathrm{For}_{i,t} + \beta_{12} \mathrm{Kospi}_{i,t} \\ & + \mathrm{ID} + \mathrm{YD} + \varepsilon_{i,t}. \end{aligned} \tag{3.3}$$

For our control variables, we go through a four-step procedure.

(1) We identify the following five key determinant categories of credit ratings based on the previous literature:

   (a) Korean Composite Stock Price Index (KOSPI) and firm performance,

   (b) business risk,

   (c) earnings management,

   (d) governance structure,

   (e) industry and year fixed effects.

TABLE 2 Continued.

(b) Variable definitions

Variable	Sign	Definition
Dependent variable:		
CR_{t+1}		Credit ratings at time $t+1$
Variables of interest:		
Relative efficiency	$+$	Technical efficiency score computed using data envelopment analysis
Absolute efficiency	$+$	Overall efficiency computed by dividing total sales revenue by total assets
Control variables:		
1. Market size and firm performance		
Kospi	$+$	Market size: takes a value of 1 if a firm is listed on KOSPI; 0 if listed on KOSDAQ
Cash performance	$+$	CFO (cashflow from operation/total assets)
Market-based performance	$+$	Earnings per share
Firm value	$+$	Tobin's Q calculated using Chung and Pruitt (1994)
2. Business risk		
Indebtedness	$-$	Debt ratio (total liabilities/total assets)
Loss	$-$	A dummy variable that takes a value of 1 if a firm's net income is negative; 0 otherwise
Market risk	$+$	ln(standard deviation of yearly stock return $\times \sqrt{\text{trading days}}$)
3. Earnings management		
AEM	$-$	Absolute value of discretionary accruals suggested by Dechow *et al* (1995)
REM	$-$	$\text{AbCFO}^*(-1) + \text{AbProd} + \text{AbSGA}^*(-1)$ suggested by Roychowdhury (2006)
4. Governance structure		
BigOwn	?	Biggest shareholder's share holdings (%)
For	$+$	Foreign investors' share holdings (%)
5. Fixed effect		
ID		Industry fixed effect
YD		Year fixed effect

Boldface denotes proxies included in our model.

(2) Under each category, we identify a median classification level, for example, we divide firm performance into (a) financial performance, (b) market performance and (c) value performance.

(3) We identify what proxies are available for each median level category. For example, under financial performance, the proxies available include: earnings per share; return on assets; return on sales; and return on equity (see Table 2).

(4) Finally, in order to examine the incremental effect of relative efficiency on credit ratings, we select the final control variable for each category that best explains our dependent variable credit ratings.

Generally, researchers select variables based on determinants without testing the validity of the proxies. However, we perform an additional step (using scatter plots and correlations) in order to select the variable that best represents each determinant category. For example, earnings per share (EPS) is generally more highly correlated with credit ratings than ROA, ROE, cash per share (CPS), etc. For robustness, we conduct our analyses after replacing our current variables with other alternatives and find that the results remain qualitatively unchanged. Note that we do not rely solely on scatter plots and correlations when choosing variables; however, we use these techniques at the final stage in order to select the variable that best represents each key determinant category. All the proxies considered as determinants are shown in Table 2(a). The proxies in boldface have been included in our model. The purpose of these additional steps is to develop the model with the highest explanatory power.

In Table 2(b), we show the expected relationship between credit ratings in period $t + 1$ and our control variables selected as proxies for our determinants. In our online appendixes, we provide additional information about variable estimation. CFO denotes cash performance calculated as the cashflow from operation divided by total assets. We expect a positive association between CR and CFO because cash-rich firms are less likely to have liquidity problems. EPS (market performance) is calculated as earnings per share divided by 1000 won for standardization. We expect EPS to be positive because firms with higher net incomes are less likely to have default risk than firms with lower net income. Lev (indebtedness) is calculated as total liabilities/total assets. We expect Lev to be negative because firms with more liabilities than assets are unlikely to adapt to financial shocks. Loss is a dummy variable that takes a value of 1 if a firm's net income is negative; Loss is expected to be negative. Vol (market risk) is calculated as the natural log of the standard deviation of the yearly stock return times the square root of the number of trading days. We expect Vol to be negative, consistent with market risk and credit risk being linked (Lim and Mali 2018). Tobin's Q (firm value) is calculated using

$$\mathrm{TQ} = \frac{\mathrm{MVCS} + \mathrm{MVPS} + \mathrm{STL} - \mathrm{STA} + \mathrm{LTD} + \mathrm{INV}}{\mathrm{TA}}, \tag{3.4}$$

where TQ denotes Tobin's Q, MVCS is the market value of common stock, MVPS is the market value of preferred stock, STL denotes short-term (current) liabilities, STA denotes short-term (current) assets, LTD denotes long-term debt, INV denotes inventory and TA denotes the total assets.

We expect to find a positive relationship between Tobin's Q and CR. Accruals earnings management (AEM) is calculated as the absolute value of discretionary accruals suggested by Dechow *et al* (1995). AEM represents a managerial strategy to increase earnings by modifying accounting treatments. We expect it to have a negative relationship with credit ratings. Managers can also influence earnings through real earnings management (REM). Roychowdhury (2006) finds evidence suggesting that managers make operational decisions in order to temporarily increase earnings by doing the following.

(1) Offering large discounts to customers to increase sales, called abnormal level of cashflow from operations (AbCFO): this increases sales, but overall the process has a negative effect on profit margins.

(2) Abnormal overproduction to report lower cost of goods sold, called abnormal level of production costs (AbProd): increasing production levels reduces production overheads and increases overall net income, but the process can increase obsolesce and storage costs.

(3) Abnormal reductions in discretionary expenses, called abnormal level of sales and general administrative expenses (AbSGA): discretionary expenses include various intangible assets not included on financial statements, including brand value and human capital. Reductions in SG&A are considered real earnings manipulation because they are required for robust day-to-day business operations.

Scrutiny by regulators is weaker for REM compared with AEM because it is difficult for legislators to detect opportunistic real earnings manipulation; thus, the cost of REM is lower. Therefore, we consider that REM would be a more desirable method for managers to influence credit ratings if they were inclined to do so. Real earnings management (REM) is calculated in the models $\text{AbCFO}^*(-1) + \text{AbProd} + \text{AbSGA}^*(-1)$ as suggested by Roychowdhury (2006) and modified by Cohen and Zarowin (2010). We expect a negative relationship between REM and credit ratings because REM is considered an opportunistic deviation from normal business practices. We also consider that NIG firms demonstrate higher levels of earnings management than IG firms, suggesting that IG firms demonstrate more robust strategic management and lower levels of opportunism than NIG firms (refer to Appendix A online for earnings management definitions).

BigOwn (governance) is the largest shareholder's share holdings calculated as a percentage, and can be positive or negative. A negative relationship would suggest large owners expropriate wealth opportunistically. A positive result would suggest large owners provide guidance and are able to break disputes between shareholders. For (governance) is calculated as foreign investors' share holdings as a percentage. For is expected to be positive because foreign investors are likely to demand stronger corporate governance. Kospi is a dummy variable that takes a value of 1 if a firm is listed on the KOSPI stock exchange and a value of 0 if the firm is listed on the Korean Securities Dealers Automated Quotations (KOSDAQ) stock exchange (see the online appendix); the KOSPI exchange is larger than KOSDAQ. Kospi has the potential to be positive or negative because we would expect larger firms to benefit from economies of scale; however, larger firms may simply have weaker internal systems and a greater potential for default. Finally, we add year and industry fixed-effect dummies.

3.2 Sample

All our data was collected from the Total Solution 2000 (TS2000), DataGuide and KISVALUE databases. These databases are similar to the WRDS package in the US and ORBIS in Europe and are analytical database programs provided by Korean Companies Information (KOCOinfor). FNguide is provided by National Information and Credit Evaluation (NICE). All three data aggregators provide financial, nonfinancial and other data for professional analysts and academics. See Appendix A online for additional information.

The sample selection process is shown in Table 3(a). We initially downloaded 23 648 nonfinancial firm observations from between 2000 and 2015. Financial firms were not initially considered for this study because the nature of their business is likely different from that of nonfinancial firms. More specifically, the inputs and outputs to calculate relative efficiency scores, the key determinants of credit ratings and the level of regulator supervision for financial firms are likely to be different from those for nonfinancial firms. Further, key financial variables were used to calculate our main control variables, such as absolute value of discretionary accruals; REM proxies are not available for financial firms.

Next, we excluded 8448 observations for firms with insufficient data to calculate efficiency scores. We excluded an additional 529 observations for firms without all the relevant financial data required to complete the analysis, leaving a final sample of 14 270. In Table 3(b), we show the number of observations per ordinal rank credit rating (as given in Table 2). As expected, credit ratings are distributed in a bell-shaped curve, with the highest number of observations (3137) being for medium-risk firms. Overall, we found there were 8666 IG firms and 6054 NIG firms. Table 3(c) shows

TABLE 3 Sample selection.

(a) Firm efficiency and credit rating sample 2000–2015

Initial CR sample	23 648
Excluding firms with insufficient observations to compute FE scores	(8 448)
Potential sample	15 200
Excluding firms with no financial data available	(480)
Final sample	14 720

(b) Sample selection by credit rating

IG			NIG		
CR scores	**Definition**	**Obs.**	**CR scores**	**Definition**	**Obs.**
10	Extremely strong	127	5	Less vulnerable	2 576
9	Very strong	1 311	4	More vulnerable	1 757
8	Strong	1 716	3	Currently vulnerable	1 081
7	Good	2 375	2	Highly vulnerable	443
6	Medium	3 137	1	Extremely vulnerable	197
Total		8 666	Total		6 054

(c) Sample selection by year

Year	**Obs.**	**Mean efficiency**	**Year**	**Obs.**	**Mean efficiency**
2000	920	0.53	2008	920	0.69
2001	920	0.56	2009	920	0.60
2002	920	0.49	2010	920	0.77
2003	920	0.63	2011	920	0.73
2004	920	0.57	2012	920	0.73
2005	920	0.46	2013	920	0.75
2006	920	0.54	2014	920	0.77
2007	920	0.57	2015	920	0.77

the levels of relative mean efficiency by firm year. Firm efficiency was 0.53 in 2000, increasing to 0.77 in 2015. We speculate that this is because of the accumulation of corporate knowledge, technological developments and market forces.

4 EMPIRICAL RESULTS

4.1 Univariate analysis

In Table 4, we provide information about the mean/median levels of our full, IG and NIG samples, and in the final column we give the results of mean/median difference tests comparing the IG and NIG samples. As we expect, we find that relative efficiency is lower for NIG than IG firms, with results that are statistically significant at the 1% significance level (t-value 7.63). We also find that absolute efficiency is different for IG firms and NIG firms (t-value 5.84). The results are consistent with IG firms demonstrating superior operational performance to NIG firms, suggesting that IG firms are able to generate more output from given inputs than NIG firms. The remainder of mean difference tests comparing the control variables of the IG and NIG firms show expected results: IG firms have higher cashflows (t-value 47.59), EPS (t-value, 32.18), Tobin's Q (t-value 29.62), large shareholders (t-value 12.15) and foreign ownership (t-value 22.69), and lower leverage (t-value -96.30), losses (t-value -62.48), volatility (t-value -29.70), accruals (t-value -20.74) and REM (t-value -16.40). While economies of scale have the potential to influence credit ratings, we find that, in a Korean context, listing on the KOSPI stock exchange compared with the KOSDAQ does not have a statistically significant influence on credit ratings. Note that the levels of earnings management for NIG firms are higher than those of IG firms. Our results suggest that distressed NIG firms are more likely to improve their efficiency levels opportunistically using earnings management.

In Table 5, we give the results of Pearson correlations. We find that credit ratings in period $t+1$ have a positive relationship with relative efficiency at the 1% significance level. This suggests relative efficiency may have additional explanatory power in explaining the relationship between efficiency and credit ratings in period $t + 1$. We find the relationship between relative efficiency and credit ratings is consistent when we use absolute efficiency. These results suggest that credit ratings increase with efficiency. All control variables show the expected sign and are consistent with our mean difference tests.

4.2 Multivariate analysis

We perform ordered probit regression in Table 6 in order to test hypothesis (H1). Model 1 shows that firms that are more efficient in turning resources into sales than their peers demonstrate higher credit ratings in the subsequent period (coefficient 0.15, z-value 5.21). In model 2, we regress absolute efficiency with credit ratings in period $t + 1$.[1] Overall, we find model 2 gives similar results to model 1: a positive

[1] For robustness, we redefine absolute efficiency as ROTA (ie, EBIT divided by total assets) and repeat all the analyses. The results remain qualitatively unchanged.

TABLE 4 Univariate analysis: descriptive statistics and difference tests (IG versus NIG). [Table continues on next page.]

	Full				IG				NIG				IG – NIG
Var	**Obs.**	**Mean (med)**	**Max (min)**	**SD**	**Obs.**	**Mean (med)**	**Max (min)**	**SD**	**Obs.**	**Mean (med)**	**Max (min)**	**SD**	t (z)
CR_{t_1}	14 671	5.85 (6.00)	10.00 (1.00)	1.90	8 614	7.46 (7.00)	10.00 (6.00)	1.10	6 054	4.00 (4.00)	5.00 (1.00)	1.09	171.02*** (104.54***)
REff	14 720	0.64 (0.79)	1.00 (0.00)	0.33	8 601	0.76 (0.82)	1.00 (0.00)	0.34	6 119	0.61 (0.73)	1.00 (0.00)	0.32	7.63*** (13.17***)
AEff	14 324	0.97 (0.87)	3.26 (0.05)	0.56	8 402	0.99 (0.90)	3.24 (0.05)	0.56	5 992	0.94 (0.83)	3.26 (0.06)	0.56	5.84*** (8.31***)
CFO	14 733	0.05 (0.05)	0.30 (−0.26)	0.09	8 617	0.07 (0.07)	0.31 (−0.14)	0.08	6 116	0.01 (0.01)	0.24 (−0.26)	0.09	47.59*** (46.72***)
EPS	14 698	1.52 (0.32)	30.08 (−7.87)	4.61	8 603	2.52 (0.65)	30.08 (−1.10)	5.24	6 095	0.12 (0.02)	11.84 (−7.87)	3.01	32.18*** (56.66***)
TQ	13 406	0.43 (0.32)	2.18 (0.03)	0.38	7 766	0.52 (0.39)	2.18 (0.07)	0.41	5 640	0.32 (0.22)	1.84 (0.03)	0.33	29.62*** (39.53***)
Lev	14 733	0.43 (0.43)	0.95 (0.04)	0.20	8 617	0.32 (0.32)	0.67 (0.04)	0.16	6 116	0.58 (0.58)	0.95 (0.18)	0.16	−96.30*** (−76.53***)

TABLE 4 Continued.

Var	Full				IG				NIG				IG – NIG
	Obs.	Mean (med)	Max (min)	SD	Obs.	Mean (med)	Max (min)	SD	Obs.	Mean (med)	Max (min)	SD	t (z)
Loss	14 736	0.23 (0.00)	1.00 (0.00)	0.42	8 617	0.07 (0.00)	1.00 (0.00)	0.25	6 119	0.46 (0.00)	1.00 (0.00)	0.49	−62.48*** (−55.56***)
Vol	13 761	58.64 (54.73)	134.54 (18.38)	23.59	7 984	53.71 (49.88)	131.59 (18.38)	21.90	5 777	65.45 (62.30)	134.54 (22.02)	24.06	−29.70*** (−30.42***)
AEM	13 922	0.07 (0.05)	0.41 (0.00)	0.08	8 133	0.06 (0.04)	0.36 (0.00)	0.07	5 789	0.09 (0.06)	0.41 (0.00)	0.09	−20.47*** (−18.02***)
REM	13 922	−(0.03) (−0.04)	1.11 (−0.69)	0.24	8 133	−0.06 (−0.07)	1.11 (−0.69)	0.25	5 789	0.01 (−0.01)	1.07 (−0.56)	0.22	−16.40*** (−24.01***)
BigOwn	14 736	0.36 (0.37)	0.79 (0.00)	0.21	8 617	0.37 (0.39)	0.79 (0.00)	0.21	6 119	0.33 (0.34)	0.79 (0.00)	0.21	12.15*** (13.54***)
Foreign	14 736	0.06 (0.01)	0.54 (0.00)	0.11	8 617	0.07 (0.01)	0.59 (0.00)	0.13	6 119	0.03 (0.00)	0.37 (0.00)	0.07	22.69*** (19.12***)
Kospi	14 736	0.50 (1.00)	1.00 (0.00)	0.50	8 617	0.50 (1.00)	1.00 (0.00)	0.50	6 119	0.50 (1.00)	1.00 (0.00)	0.50	0.23 (0.24)

t indicates the t-value for the mean-difference test. z indicates the Wilcoxon z-value for the median-difference test. *, ** and *** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively. See Table 2 for the definitions of the variables.

TABLE 5 Pearson correlations.

	CR	REff	AEff	CFO	EPS	TQ	Lev
CR	1						
REff	0.10***	1					
AEff	0.03***	0.12***	1				
CFO	0.42***	0.11***	0.18***	1			
EPS	0.31***	0.03***	0.06***	0.21***	1		
TQ	0.31***	0.08***	−0.10***	0.09***	0.06***	1	
Lev	−0.75***	−0.03***	0.23***	−0.14***	−0.12***	−0.38***	1
Loss	−0.53***	−0.09***	−0.17***	−0.35***	−0.32***	−0.02**	0.22***
Vol	−0.30***	−0.11***	−0.02***	−0.20***	−0.18***	−0.02**	0.18***
AEM	−0.22***	−0.01	0.04***	−0.13***	−0.08***	0.05***	0.15***
REM	−0.16***	0.01*	−0.17***	−0.41***	0.01	0.03***	−0.00
BigOwn	0.11***	−0.02**	0.02**	0.02***	−0.01*	−0.18***	−0.08***
For	0.22***	−0.00	−0.04***	0.13***	0.03***	0.20***	−0.14***
Kospi	0.00	−0.10***	−0.03***	0.03***	0.19***	−0.21***	0.10***

	Loss	Vol	AEM	REM	BigOwn	For	Kospi
Loss	1						
Vol	0.23***	1					
AEM	0.22***	0.31***	1				
REM	0.16***	0.13***	0.12***	1			
BigOwn	−0.12***	−0.14***	−0.12***	−0.06***	1		
For	−0.11***	−0.23***	−0.09***	0.02***	0.03***	1	
Kospi	−0.08***	−0.24***	−0.17***	−0.03***	0.02***	0.21***	1

*, ** and *** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively. See Table 2 for the definitions of the variables.

relationship between absolute efficiency and CR (coefficient 0.44, z-value 24.16). In model 3, we find a positive relationship between CR in period $t+1$ and relative efficiency after adjusting for absolute efficiency (coefficient 0.07, z-value 2.66). We find evidence consistent with (H1): there is a positive relationship between relative efficiency and credit ratings in the subsequent year. In addition, our findings add to the current debate about whether relative efficiency calculated using frontier analysis has additional explanatory power. We find that, after adjusting for absolute efficiency, relative efficiency has incremental explanatory power in explaining the relationship between relative firm efficiency and credit ratings.

The results are consistent with credit rating agencies having the sophistication to interpret a firm's ability to generate sales from given resources. The positive association between relative efficiency and credit ratings suggests a negative relationship between relative operational performance and potential default risk from

TABLE 6 Influence of firm efficiency on credit ratings using efficiency score: results of ordered probit regression analysis.

	Sign	Model 1	Model 2	Model 3
REff	+	0.15*** (5.21)		0.07*** (2.66)
AEff	+		0.45*** (24.60)	0.44*** (24.16)
CFO	+	0.429*** (34.50)	4.16*** (33.41)	4.13*** (33.07)
EPS	+	0.03*** (12.96)	0.03*** (12.65)	0.03*** (12.72)
Tobin Q	+	0.17*** (6.17)	0.18*** (6.59)	0.18*** (6.46)
Lev	−	−6.86*** (−96.56)	−7.41*** (−98.19)	−7.41*** (−98.12)
Loss	−	−1.40*** (−51.27)	−1.35*** (−49.27)	−1.35*** (−49.04)
Vol	−	−0.00*** (−9.71)	−0.00*** (−9.97)	−0.01*** (−9.51)
AEM	−	−0.58*** (−4.75)	−0.79*** (−6.44)	−0.79*** (−6.43)
REM	−	−0.32*** (−7.30)	−0.19*** (−4.43)	−0.20*** (−4.64)
BigOwn	?	0.30*** (6.06)	0.23*** (4.64)	0.24*** (4.79)
For	+	0.99*** (11.14)	1.03*** (11.55)	1.03*** (11.49)
Kospi	?	0.00 (0.21)	0.03 (1.46)	0.03* (1.69)
YD		Included	Included	Included
ID		Included	Included	Included
χ^2		19 040.21***	19 663.74***	19 623.84***
Pseudo R^2		0.3578	0.3691	0.3689
Obs.		13 075	13 090	13 074

*, ** and *** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively. Figures in parentheses indicate z-values. See Table 2 for variable definitions. Model:

$$\begin{aligned}\mathrm{CR}_{i,t+1} = {}& \beta_1 \mathrm{REff}_{i,t} + \beta_2 \mathrm{AEff}_{i,t} + \beta_3 \mathrm{CFO}_{i,t} + \beta_4 \mathrm{TQ}_{i,t} + \beta_5 \mathrm{Lev}_{i,t} + \beta_6 \mathrm{Loss}_{i,t} \\ & + \beta_7 \mathrm{Vol}_{i,t} + \beta_8 \mathrm{AEM}_{i,t} + \beta_9 \mathrm{REM}_{i,t} + \beta_{10} \mathrm{BigOwn}_{i,t} + \beta_{11} \mathrm{For}_{i,t} + \beta_{12} \mathrm{Kospi}_{i,t} + \mathrm{ID} + \mathrm{YD} + \varepsilon_{i,t}.\end{aligned}$$

the credit rating agency's perspective. Management makes strategic decisions in order to maximize sales from available resources to optimize efficiency. A firm may increase efficiency by increasing sales though effective advertising, marketing and promotional activities, the ability to understand customers and market trends, and the ability to adopt enhanced systems and technologies. Moreover, managers can increase efficiency by utilizing resources and by optimizing R&D, administration costs and human capital costs. Further, effective firms are likely to optimize efficiency with robust production and operational systems that minimize waste. Our data suggests that relative efficiency is a potential signal of a firm's effective strategic decision making relative to their peers, which is captured by a firm's credit ratings.[2] Consistent with our univariate tests and Pearson correlations, all of our control variables apart from Kospi demonstrate the expected sign at the 1% significance level.

5 ADDITIONAL ANALYSIS

5.1 Decile rank of relative efficiency

For robustness, we perform ordered probit regression using the decile rank of relative efficiency, using efficiency scores from 1 to 10, with 10 being the highest level of efficiency, or the efficiency closest to the maximum efficiency frontier. Model 1 in Table 2 shows that relative efficiency is associated with credit ratings when we use the decile rank of efficiency scores (coefficient 0.07, z-value 19.85). In model 2, we find that relative efficiency has incremental explanatory power to explain the relationship between credit ratings and efficiency after adjusting for absolute efficiency (coefficient 0.05, z-value 13.66). Taken together, the results from Tables 6 and 7 suggest that relative efficiency could be included as a key determinant when estimating credit ratings, and that relative efficiency may influence a credit rating agency's perception of credit risk.

5.2 IG versus NIG

In (5.1), we add the dummy variable IG, which takes a value of 1 if a firm is above the investment-grade threshold (A$-$ and above) and 0 if a firm is below the IG threshold

[2] Due to market forces, relative efficiency may not be consistent over time, owing to the accumulation of corporate knowledge and technological developments. For robustness, we cross-sectionally estimate relative efficiency for each year in the data set and examine the relationship between credit ratings in period $t + 1$ and relative efficiency for each year in the data set using the technique suggested by Fama and MacBeth (1973). Tabulated results are consistent with previous findings.

TABLE 7 Influence of firm efficiency on credit ratings using decile rank.

	Sign	Model 1	Model 2
REff_decile	+	0.07***	0.05***
		(19.85)	(13.66)
AEff	+		0.38***
			(19.94)
CFO	+	4.10***	4.01***
		(32.83)	(32.04)
EPS	+	0.03***	0.03***
		(12.91)	(12.72)
Tobin Q	+	0.14***	0.16***
		(5.23)	(5.70)
Lev	−	−6.93***	−7.38***
		(−96.99)	(−97.55)
Loss	−	−1.28***	−1.27***
		(−45.78)	(−45.24)
Vol	−	−0.00***	−0.00***
		(−9.91)	(−9.61)
AEM	−	−0.72***	−0.86***
		(−5.88)	(−7.00)
REM	−	−0.27***	−0.19***
		(−6.31)	(−4.39)
BigOwn	?	0.27***	0.23***
		(5.45)	(4.57)
For	+	0.94***	0.98***
		(10.50)	(11.01)
Kospi	?	0.02	0.04**
		(0.83)	(2.01)
YD		Included	Included
ID		Included	Included
χ^2		19 408.20***	19 803.60***
Pseudo R^2		0.3648	0.3722
Obs.		13 075	13 074

*, ** and *** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively. Figures in parentheses indicate z-values. REff_decile denotes the decile rank of relative efficiency score from 1 to 10, where 10 is the highest. See Table 2 for variable definitions. Model:

$$\mathrm{CR}_{i,t+1} = \beta_1 \mathrm{REff\_decile}_{i,t} + \beta_2 \mathrm{AEff}_{i,t} + \beta_3 \mathrm{CFO}_{i,t} + \beta_4 \mathrm{TQ}_{i,t} + \beta_5 \mathrm{Lev}_{i,t} + \beta_6 \mathrm{Loss}_{i,t} + \beta_7 \mathrm{Vol}_{i,t} + \beta_8 \mathrm{AEM}_{i,t} + \beta_9 \mathrm{REM}_{i,t} + \beta_{10} \mathrm{BigOwn}_{i,t} + \beta_{11} \mathrm{For}_{i,t} + \beta_{12} \mathrm{Kospi}_{i,t} + \mathrm{ID} + \mathrm{YD} + \varepsilon_{i,t}.$$

TABLE 8 Comparative analysis of investment-grade versus non-investment-grade firms.

	Sign	**Model 1**	**Model 2**
REff	+	0.08*** (4.17)	0.07** (2.22)
IG	+	1.40*** (69.25)	1.24*** (38.21)
REffIG	+		0.26*** (6.32)
AEff	+	0.24*** (18.39)	0.24*** (18.51)
CFO	+	2.39*** (26.94)	2.38*** (26.87)
EPS	+	0.02*** (11.02)	0.02*** (11.03)
Tobin Q	+	0.12*** (6.29)	0.12*** (6.15)
Lev	–	–4.33*** (–89.99)	–4.33*** (–90.01)
Loss	–	–0.75*** (–39.29)	–0.75*** (–39.39)
Vol	–	–0.00*** (–8.24)	–0.00*** (–8.44)
AEM	–	–0.58*** (–6.61)	–0.59*** (–6.80)
REM	–	–0.12*** (–3.80)	–0.12*** (–3.83)
BigOwn	?	0.11*** (3.09)	0.12*** (3.21)
For	+	0.62*** (9.68)	0.62*** (9.71)
Kospi	?	0.02 (1.41)	0.02 (1.46)
YD		Included	Included
ID		Included	Included
χ^2		26891.45***	26932,70***
Pseudo R^2		0.5055	0.5062
Obs.		13 074	13 074

*, ** and *** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively. Figures in parentheses indicate z-values. See Table 2 for variable definitions. Model:

$$\begin{aligned}\mathrm{CR}_{i,t+1} = {} & \beta_1 \mathrm{REff}_{i,t} + \beta_2 \mathrm{IG}_{i,t} + \beta_3 \mathrm{REffIG}_{i,t} + \beta_4 \mathrm{AEff}_{i,t} + \beta_5 \mathrm{CFO}_{i,t} \\ & + \beta_6 \mathrm{TQ}_{i,t} + \beta_7 \mathrm{Lev}_{i,t} + \beta_8 \mathrm{Loss}_{i,t} + \beta_9 \mathrm{Vol}_{i,t} + \beta_{10} \mathrm{AEM}_{i,t} + \beta_{11} \mathrm{REM}_{i,t} + \beta_{12} \mathrm{BigOwn}_{i,t} \\ & + \beta_{13} \mathrm{For}_{i,t} + \beta_{14} \mathrm{Kospi}_{i,t} + \mathrm{ID} + \mathrm{YD} + \varepsilon_{i,t}.\end{aligned}$$

TABLE 9 Influence of firm efficiency on credit ratings: IG versus NIG. [Table continues on next page.]

	IG					NIG			
	Sign	**Model 1**	**Model 2**	**Model 3**		**Sign**	**Model 1**	**Model 2**	**Model 3**
REff	+	0.27***		**0.22*****	REff	+	−0.02		**−0.11****
		(6.87)		**(5.62)**			(−0.40)		**(−2.08)**
AEff	+		0.38***	0.37***	AEff	+		0.40***	0.41***
			(13.83)	(13.20)				(13.24)	(13.39)
CFO	+	3.92***	3.80***	3.71***	CFO	+	3.22***	3.18***	3.21***
		(20.66)	(19.98)	(19.42)			(15.71)	(15.45)	(15.56)
EPS	+	0.02***	0.02***	0.02***	EPS	+	0.05***	0.05***	0.05***
		(7.36)	(7.27)	(7.37)			(7.75)	(7.43)	(7.46)
Tobin Q	+	0.19***	0.22***	0.21***	Tobin Q	+	−0.06	−0.06	−0.06
		(5.25)	(6.02)	(5.69)			(−1.13)	(−1.20)	(−1.13)
Lev	−	−5.87***	−6.48***	−6.47***	Lev	−	−6.12***	−6.54***	−6.53***
		(−53.51)	(−54.09)	(53.95)			(−46.96)	(−48.43)	(−48.32)
Loss	−	−1.47***	−1.47***	−1.44***	Loss	−	−1.01***	−0.96***	−0.96***
		(−24.29)	(−24.28)	(−23.88)			(−25.95)	(−24.61)	(−24.66)
Vol	−	−0.01***	−0.01***	−0.01***	Vol	−	−0.00***	−0.00***	−0.00***
		(−8.35)	(−8.99)	(−8.17)			(−3.41)	(−3.05)	(−3.35)
AEM	−	−1.19***	−1.48***	−1.50***	AEM	−	−0.18	−0.26***	−0.26
		(−5.83)	(−7.15)	(−7.22)			(−1.06)	(−1.46)	(−1.49)

TABLE 9 Continued.

	IG					NIG			
	Sign	**Model 1**	**Model 2**	**Model 3**		**Sign**	**Model 1**	**Model 2**	**Model 3**
REM	–	−0.27***	−0.16***	−0.18***	REM	–	−0.24***	−0.15*	−0.14*
		(−4.75)	(−2.71)	(−3.21)			(−3.05)	(−1.89)	(−1.72)
BigOwn	?	0.23***	0.17**	0.19***	BigOwn	?	0.18**	0.11	0.11
		(3.35)	(2.38)	(2.76)			(2.23)	(1.37)	(1.33)
For	+	0.77***	0.78***	0.79***	For	+	0.81***	0.84***	0.83***
		(7.01)	(7.17)	(7.23)			(3.85)	(3.99)	(3.92)
Kospi	?	−0.02	−0.01	0.01	Size	?	0.05	0.07**	0.06**
		(−0.62)	(−0.21)	(0.50)			(1.62)	(2.20)	(2.01)
YD		Included	Included	Included	YD		Included	Included	Included
ID		Included	Included	Included	ID		Included	Included	Included
χ^2		4825.69***	4996.37***	4999.40***	χ^2		4091.47***	4268.85***	4273.19***
Pseudo R^2		0.2326	0.2402	0.2410	Pseudo R^2		0.2787	0.2909	0.2912
Obs.		7591	7591	7591	Obs.		5483	5483	5483

*, ** and *** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively. Figures in parentheses indicate z-values. See Table 2 for variable definitions. Model:

$$\begin{aligned}\mathrm{CR}_{i,t+1} &= \beta_1\mathrm{REff}_{i,t} + \beta_2\mathrm{AEff}_{i,t} + \beta_3\mathrm{CFO}_{i,t} + \beta_4\mathrm{TQ}_{i,t} + \beta_5\mathrm{Lev}_{i,t} + \beta_6\mathrm{Loss}_{i,t} + \beta_7\mathrm{Vol}_{i,t} \\ &\quad + \beta_8\mathrm{AEM}_{i,t} + \beta_9\mathrm{REM}_{i,t} + \beta_{10}\mathrm{BigOwn}_{i,t} + \beta_{11}\mathrm{For}_{i,t} + \beta_{12}\mathrm{Kospi}_{i,t} + \mathrm{ID} + \mathrm{YD} + \varepsilon_{i,t}.\end{aligned}$$

(BBB+ and below):

$$\begin{aligned}R^*_{i,t+1} = {} & \beta_1\mathrm{REff}_{i,t} + \beta_2\mathrm{IG}_{i,t} + \beta_3\mathrm{REffIG}_{i,t} + \beta_4\mathrm{AEff}_{i,t} + \beta_5\mathrm{CFO}_{i,t} \\ & + \beta_6\mathrm{TQ}_{i,t} + \beta_7\mathrm{Lev}_{i,t} + \beta_8\mathrm{Loss}_{i,t} + \beta_9\mathrm{Vol}_{i,t} + \beta_{10}\mathrm{AEM}_{i,t} \\ & + \beta_{11}\mathrm{REM}_{i,t} + \beta_{12}\mathrm{BigOwn}_{i,t} + \beta_{13}\mathrm{For}_{i,t} + \beta_{14}\mathrm{Size}_{i,t} \\ & + \mathrm{ID} + \mathrm{YD} + \varepsilon_{i,t}. \end{aligned} \tag{5.1}$$

Our variable of interest is the interaction term $\mathrm{REffIG}_{i,t}$, which shows a different relationship between firm efficiency and credit rating in period $t+1$ for both NIG and IG samples. In model 1 in Table 8, we again find that, after controlling for absolute efficiency, relative efficiency has explanatory power to explain the overall relationship between credit ratings and operational efficiency. However, in model 2, when we interact relative efficiency with our IG dummy, we find that the relationship between efficiency and credit ratings is stronger for IG firms.

The IG firms at the optimum efficiency frontier demonstrate the best corporate performance and most robust systems. Consequently, in hypothesis (H2), we consider whether the relationship between relative efficiency and credit ratings is equal or different for NIG and IG. On the one hand, NIG firms may be rewarded for minimizing expenditure on resources. On the other hand, credit rating agencies may consider NIG firms less likely to have the ability to maximize sales than IG groups. Thus, higher efficiency could be seen as an opportunistic form of earnings management by the firm in order to meet financial targets to position themselves closer to the efficiency frontier horizon.

Our results suggest that NIG firms with higher relative efficiency are more likely to achieve a lower credit rating in the subsequent period, suggesting they are more likely to be perceived as having an increased potential to default by rating agencies. We speculate that the different relationships between relative efficiency and credit ratings for the NIG and IG samples may be due to NIG firms being required to sacrifice expenditure on resources in order to meet targets to move closer to the optimum efficiency frontier (as suggested by the negative relationship between credit ratings and accruals and REM). NIG managers may manipulate input by reducing necessary expenditures (including advertising and R&D) and downsizing the workforce; as a result, credit rating agencies may capture this behavior and impose penalties accordingly.

5.3 Independent IG/ING analysis

Next, we perform ordered probit regression independently for 7591 NIG and 5483 IG observations, respectively. Model 3 in Table 9 shows that, after controlling for absolute efficiency, relative efficiency has incremental explanatory power in our ordered probit regression for both NIG and IG samples. Interestingly, there is a different directional relationship between relative efficiency and credit ratings in period $t + 1$ for the NIG and IG samples. We consistently find a positive relationship between relative efficiency and credit ratings in period $t + 1$ for the IG sample. However, we find a negative relationship between relative efficiency and credit ratings for NIG firms (coefficient -0.11, z-value -2.08). While we expected to find a different relationship between firm efficiency and credit ratings, a negative relationship between firm efficiency and subsequent credit ratings provides additional explanatory power.[3] Again, we surmise this result may be because NIG firms have the potential for inferior management and less robust operational systems. Thus, to satisfy stakeholders, NIG firms may make short-term decisions in order to manage operational performance, which may have a negative influence on future credit ratings, because the results suggest credit rating agencies have the sophistication to interpret a firm's relative efficiency differently for NIG and IG firms.

5.4 Sensitivity analysis

We estimate the investment-grade group as being above BBB+, an ordinal rank of 5 or higher (see our ordinal rankings in Table 1). However, different investors have different risk criteria. Thus, we perform sensitivity analysis in order to redefine the investment-grade threshold in seven different ways: we developed seven separate models, in which each investment grade was defined differently. Table 10 provides the results of our analysis (we only include the coefficient and significance level for credit ratings in period $t + 1$, for brevity) and lists our redefined IG samples: investment grade column IG6 lists our redefined IG sample set at an original score of 6 (IG was defined as 5 in our main analysis). Thus, non-investment-grade IG6 also increases the ordinal score of our NIG sample to 5 (NIG was defined as 4 in our main analysis). We repeat this process for various IG/NIG ordinal scores (see the notes in Table 10). Table 10 provides evidence that relative firm efficiency is positively associated with credit ratings in the subsequent period for our new IG/NIG status, indicating that relative efficiency has useful information in predicting future credit ratings for our modified investment-grade sample. Moreover, we also find a negative relationship for the NIG sample. Both results are consistent with our main findings.

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[3] For robustness, we repeated our analyses using SFA based on the Malmquist efficiency index calculation technique (see Coelli *et al* 2005). Our results suggest that overall there is a positive relationship between credit ratings in period $t + 1$ and firm efficiency. Moreover, there are different relationships between firm efficiency and subsequent credit ratings for riskier NIG firms and less risky IG firms.

TABLE 10 Sensitivity analysis.

(a) IG

	IG8	IG7	IG6	IG5	IG4	IG3
REff	**0.21*****	**0.22*****	**0.22*****	**0.16*****	**0.12*****	**0.08*****
***z*-value**	**(2.92)**	**(4.31)**	**(5.62)**	**(4.89)**	**(4.04)**	**(2.76)**
Control	Included	Included	Included	Included	Included	Included
ID and YD	Included	Included	Included	Included	Included	Included
χ^2	346.67***	1 868.07***	4 999.40***	9 424.48	13 713.09***	16 638.81***
Pseudo R^2	0.0830	0.1730	0.2410	0.2992	0.3366	0.3489
Obs.	2 736	4 835	7 591	9 901	11 491	12 487

(b) NIG

	IG8	IG7	IG6	IG5	IG4	IG3
REff	**−0.01**	**−0.08****	**−0.11****	**−0.13***	**−0.08**	**−0.29**
***z*-value**	**(−0.31)**	**(−2.14)**	**(−2.08)**	**(−1.89)**	**(−0.73)**	**(−1.34)**
Control	Included	Included	Included	Included	Included	Included
ID and YD	Included	Included	Included	Included	Included	Included
χ^2	12 447.29***	8 525.98***	4 273.19***	1 799.88***	698.53***	160.55***
Pseudo R^2	0.3495	0.3386	0.2912	0.2496	0.2483	0.2214
Obs.	10 338	8 239	5 483	3 173	1 583	587

*, ** and *** denote statistical significance at the 10%, 5% and 1% confidence levels, respectively. Figures in parentheses indicate z-values. All control variables are the same as in the main analysis. IG8 = 1 if a credit rating at time $t+1$ is greater than 7. IG7 = 1 if a CR at time $t+1$ is greater than 6, and IG4 = 1 if a CR at time $t+1$ is greater than 3. Model:

$$\begin{aligned}\mathrm{CR}_{i,t+1} = {}& \beta_1\mathrm{REff}_{i,t} + \beta_2\mathrm{AEff}_{i,t} + \beta_3\mathrm{CFO}_{i,t} + \beta_4\mathrm{TQ}_{i,t} + \beta_5\mathrm{Lev}_{i,t} + \beta_6\mathrm{Loss}_{i,t} \\ & + \beta_7\mathrm{Vol}_{i,t} + \beta_8\mathrm{AEM}_{i,t} + \beta_9\mathrm{REM}_{i,t} + \beta_{10}\mathrm{BigOwn}_{i,t} + \beta_{11}\mathrm{For}_{i,t} + \beta_{12}\mathrm{Kospi}_{i,t} + \mathrm{ID} + \mathrm{YD} + \varepsilon_{i,t}.\end{aligned}$$

5.5 Credit rating at time t

We used credit ratings at time $t + 1$ as the dependent variable for all of the analyses in our study, because rating agencies use annual financial statement data in order to measure a firm's credit rating and are forward-looking. However, it is also possible that the influence of current efficiency on future default probability should be captured in period t. To add robustness, we conducted additional analysis after replacing credit ratings one period ahead ($t + 1$) with contemporaneous ones (t). Our results (untabulated) suggest these are consistent.

6 CONCLUSIONS

We performed empirical tests to establish whether relative efficiency calculated using frontier analysis (ie, DEA) has the potential to explain the relationship between efficiency and credit ratings. We consider relative efficiency to be the manifestation of a firm's operational performance, as a direct result of strategic decision making. Consequently, we questioned whether or not operational performance, proxied by relative efficiency, influences a credit rating agency's potential of risk, proxied by credit ratings. Our results suggest that, after adjusting for absolute efficiency, relative efficiency has a positive relationship with credit ratings in period $t + 1$. These results suggest that firms with the most effective management strategies to improve technical efficiency and operational efficiency likely have higher credit ratings in the subsequent period and demonstrate that credit rating agencies are sophisticated enough to capture the ability of firms to generate sales (output) by utilizing limited resources (input) and capture this information in a firm's credit rating in period $t + 1$. Our results are consistent when we test the relationship between relative efficiency and credit ratings in period t. The role of credit agencies is to provide market participants with information about whether a firm will likely survive through the business cycle. Our results are consistent with credit rating agencies judging that firms that are more efficient are more likely to withstand stressful macroeconomic conditions.

When we partition our sample into IG and NIG, we find different results. The relationship between relative efficiency and credit ratings remains positive for IG firms and the full sample; however, the relationship between firm efficiency and credit ratings is negative for the NIG sample. NIG firms may minimize required inputs in order to meet financial targets. For example, given that frontier analysis establishes an optimum efficiency frontier within an industry, an NIG firm may reduce its expenditure on required expenses, such as R&D, in order to maximize its efficiency ratio. Consequently, NIG firms have the potential to move closer to the optimal efficiency frontier horizon. However, this position could be considered differently for both samples. We conjecture that movement toward the optimal efficiency frontier for the IG sample is a demonstration of effective operational performance and strategic management. However, it has the potential to be viewed as weak operational performance as a result of economic distress for the NIG sample, and penalties may be imposed on such behavior.

The results of this study are important for numerous reasons. First, we find that relative efficiency has a positive influence on credit ratings for the IG sample as well as our full sample. This finding could have important implications: relative efficiency is a proxy for operational performance. Higher operational performance demonstrates that management is effective. We find evidence that credit rating agencies are able to capture this information and include it in their credit rating. Rating agencies are interested in whether a firm is likely to survive through the business cycle, and judge that an efficient firm is more likely to withstand difficult economic conditions. Second, there is a growing interest as to whether relative efficiency has implicit advantages compared with absolute efficiency for modeling purposes. We find evidence that relative efficiency and absolute efficiency can be used in our model, suggesting both measures provide relevant information for modeling purposes. Finally, we find that the relationship between relative efficiency and credit ratings is different for NIG and IG samples. We surmise that the differences are potentially due to movements toward the efficiency frontier representing financial distress or a form of opportunism to meet financial targets at the expense of robust operational performance for the NIG sample. Future studies may extend our findings and consider the opportunistic mechanism that facilitates the different relationships between relative efficiency and credit ratings for investment-grade and non-investment-grade firms.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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